# Data Mining Lab, Exercise 6

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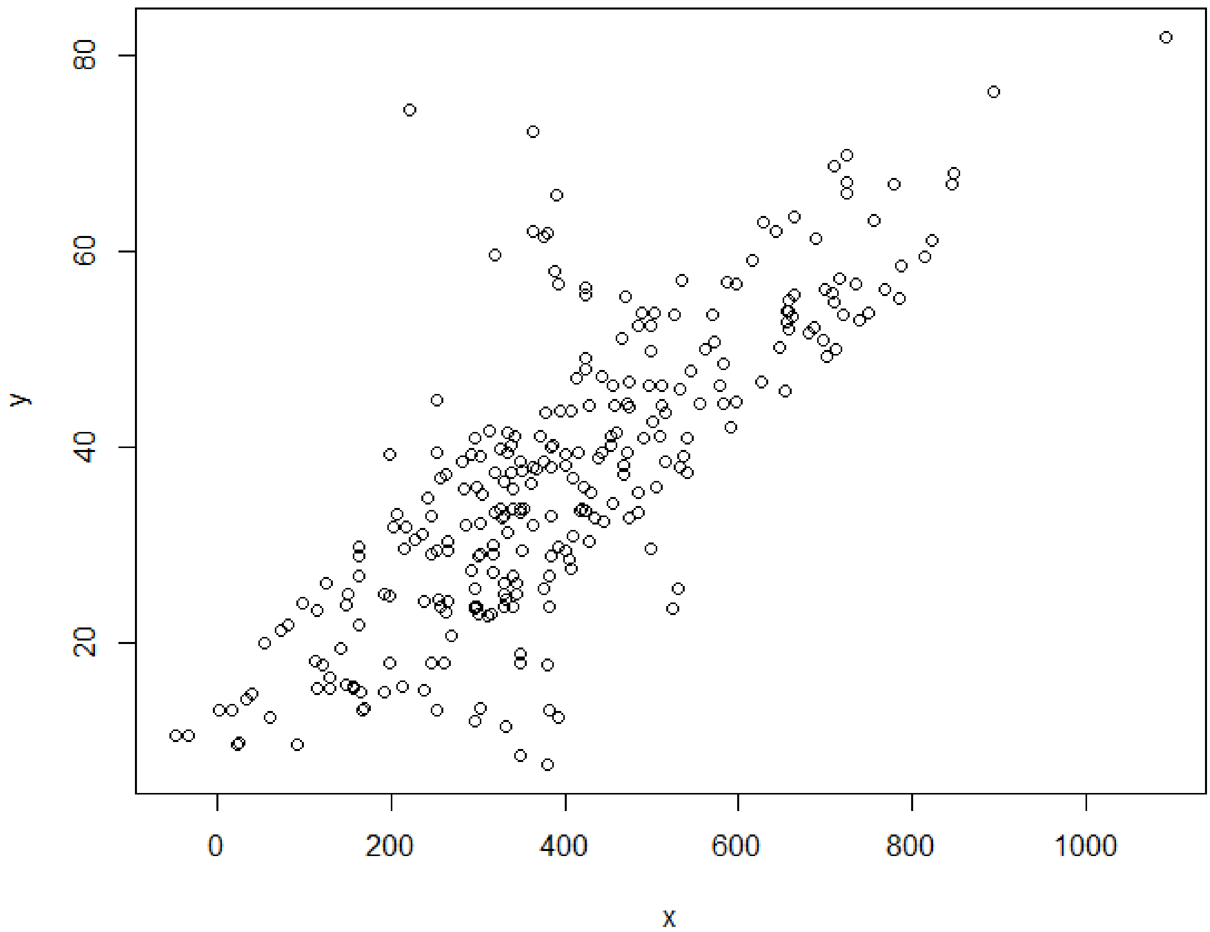
Dataset: ConcreteData.csv

In the dataset the possible linear relationship is between “Cement” (**X**) and “Concrete compressive strength” (**Y**). The scatter plot shows it very clearly.

```
> d<-read.csv(file="ConcreteData.csv")
> make.names(names(d))
> x<-d$Cement
> y<-d$Concrete.compressive.strength
plot(x,y)
```




## Tasks 1

Use regression to estimate Y based on a single predictor X.

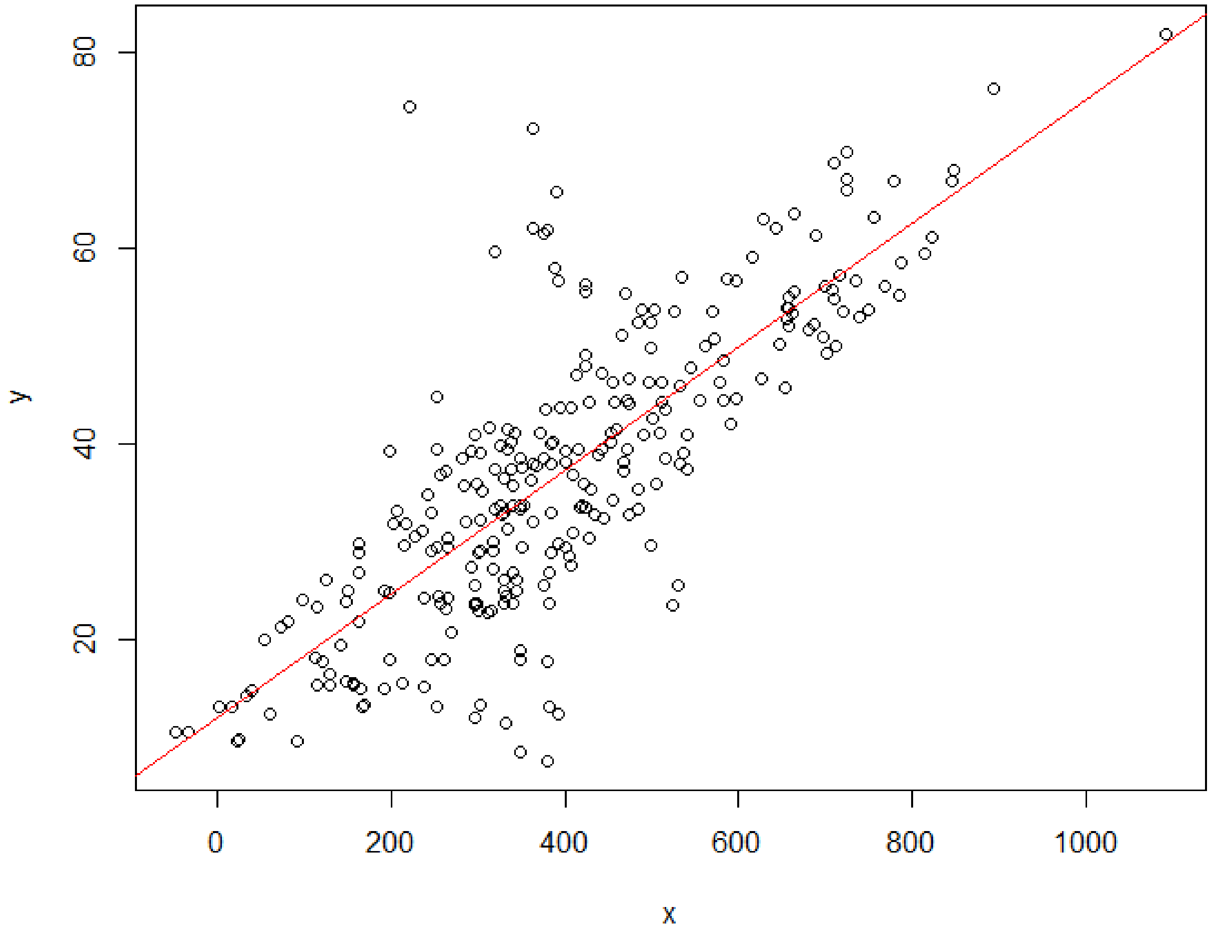
a) What is the estimated regression equation (ERE)?

```
> model<-lm(y ~ x)
> summary(model)

Call:
lm(formula = y ~ x)

Residuals:
    Min      1Q  Median      3Q     Max 
-28.295  -5.624  -0.145   5.001  48.260 
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 12.066387   1.296877   9.304   <2e-16 ***
x            0.063101   0.002927  21.556   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.308 on 277 degrees of freedom
Multiple R-squared:  0.6265,	Adjusted R-squared:  0.6252 
F-statistic: 464.6 on 1 and 277 DF,  p-value: < 2.2e-16
```

Based on the summary(model) output the **ERE** is: **y = 12.066387 +** `0.063101 * x`

b) A scatter plot of “Cement” vs. “Concrete compressive strength” and the line of ERE.




c) What would be a typical prediction error (residual standard error) obtained using the created model to predict Y.

The RSE value is 9.308. The observed values deviate from the predicted values by ~9.308.

d) Does the linear relationship exist between X and Y?

Assuming the regression formula is y = B0 + B1 * x + E. To answer is linear regression exists, we should test the following hypothesis:

- H0: B1 = 0. No relationship between x and y.
- Ha: B1 != 0. Linear relationship between x and y.

We can test "null hypothesis" because we have p-value less than < 2.2e-16, which is close to 0. If p-value is such small (< 0.05), the hypothesis H0 is rejected.

e) How closely does the model fit the data?

We should use the coefficient of determination. The $R^2$ (Coefficient of determination) value of our model is 0.6265. Not very close 1, but still good enough.

f) For new values of X find the estimates of response Y. Find the 95% confidence interval for the true mean Y and find the 95% prediction interval for a randomly chosen value of Y. Perform the calculations for all new values of Y. What can you observe?

Let's take new Cement values as 198.6, 412.8 and 616.4.

Determining confidence intervals:

```
> new <- data.frame((x = c(198.6,412.8, 616.4)))
> pred.conf <- predict(model, new, interval="confidence", level=0.95)
> pred.conf
       fit      lwr      upr
1 24.59823 23.00109 26.19537
2 38.11445 37.01504 39.21386
3 50.96180 49.30114 52.62246
```

Column "fit" is the predicted values. Column "lwr" is the lower bound of the confidence interval. Column "upr" is the upper bound of the confidence interval.

Prediction intervals:

```
> pred.pred <- predict(model, new, interval="prediction", level=0.95)
> pred.pred
       fit       lwr      upr
1 24.59823  6.206153 42.99031
2 38.11445 19.758895 56.47000
3 50.96180 32.564095 69.35950
```

Prediction intervals are wider than confidence intervals.

Let's evaluate the model on the real data.

```
> p <- predict(model, new)  # estimated  values of Y for new values of X
> q <- c(24.89, 47.13, 59)  # true values of Y for new values of X
>
> sse <- sum((q - p)^2)
> sst <- sum((y-mean(y))^2)
> pseudo_r2 <- 1 - sse/sst
> pseudo_r2
[1] 0.997728
```

The closer to 1 the better, so we have very good result.

## Task 2

Use multiple regression to estimate Y based on several predictors X.

```
> x1<-d$Cement
> x2<-d$Blast.Furnace.Slag
> mult_model <- lm(y ~ x1+x2)
> summary(mult_model)

Call:
lm(formula = y ~ x1 + x2)

Residuals:
     Min       1Q   Median       3Q      Max
-22.4959  -4.8970  -0.3651   4.9933  31.1790

Coefficients:
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.130370   1.764375  -1.207    0.228
x1           0.047632   0.002908  16.379   <2e-16 ***
x2           0.173764   0.016847  10.314   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.922 on 276 degrees of freedom
Multiple R-squared:  0.7304,	Adjusted R-squared:  0.7285
F-statistic: 373.9 on 2 and 276 DF,  p-value: < 2.2e-16
```

a) What is the estimated regression equation?

ERE is: **Y = -2. 130370 + 0.047632 * x1 + 0.173764 * x2**

b) Compare $R^2$ values from the multiple regression and the regression done in Task 1.

The $R^2$ for the multiple linear regression is 0.7304, which is better than 0.6265 coefficient of determination from Task 1.

The Residual standard error 7.922 is also better than RSE value 9.308 from Task 1.